Final Project

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May 13, 2017

Contents

1 Variable

Pick one of the quantitative independent variables from the training data set (train.csv), and define that variable as X.

Pick SalePrice as the dependent variable, and define it as Y for the next analysis.

1.1 Variable Picked

> The variable we will set to X is LotArea, which is defined as the Lot size in square feet. I chose LotArea because an anecdotal assumption is that the larger the lot size is the higher the sale price. However, living in NYC, I know that tiny lots in very desirable places have sold for a high price so I believe there may be some interesting varability.

```
library(tidyverse)
train.df <- as_tibble(read.csv(paste("https://raw.githubusercontent.com/", "ChristopheHunt/",
    "MSDA---Coursework/master", "/Data%20605/Final%20Project/train.csv", sep = "")))
```

```
sub.train.df <- train.df[, c("SalePrice", "LotArea")]
```

2 Probability

Calculate as a minimum the below probabilities a through c.

Assume the small letter "x" is estimated as the 4th quartile of the X variable, and the small letter "y" is estimated as the 2nd quartile of the Y variable. Interpret the meaning of all probabilities.

```
prob.x <- list(qrt = as.numeric(quantile(sub.train.df$LotArea)[4]))

prob.y <- list(qrt = as.numeric(quantile(sub.train.df$SalePrice)[2]))
```

```
prob.y.x <- sub.train.df %>% mutate(greaterLotArea = ifelse(LotArea >= prob.x$qrt, 1, 0),
                                     lesserLotArea = ifelse(LotArea < prob.x$qrt, 1, 0),
                                     greaterSalePrice = ifelse(SalePrice >= prob.y$qrt,1, 0),
                                     lesserSalePrice = ifelse(SalePrice < prob.y$qrt,1, 0))
```

2.1 a. $P(X > x|Y > y)$

```
a <- (sum(ifelse(prob.y.x$greaterLotArea == 1 &
                  prob.y.x$greaterSalePrice == 1, 1, 0))
      / nrow(prob.y.x)) / ((sum(prob.y.x$greaterLotArea) / nrow(prob.y.x)))
a
```

```
## [1] 0.9369863
```

2.2 b. $P(X > x, Y > y)$

```
b <- sum(ifelse(prob.y.x$greaterLotArea == 1 &
                 prob.y.x$greaterSalePrice == 1, 1, 0))/nrow(prob.y.x)
b
```

```
## [1] 0.2342466
```

2.3 c. $P(X < x|Y > y)$

```
c <- (sum(ifelse(prob.y.x$lesserLotArea == 1 &
                  prob.y.x$greaterSalePrice == 1, 1, 0))
      / nrow(prob.y.x)) / ((sum(prob.y.x$lesserLotArea) / nrow(prob.y.x)))
c
```

```
## [1] 0.6876712
```

Does splitting the training data in this fashion make them independent?

In other words, does $P(X|Y) = P(X)P(Y)$?

> I am understanding this to mean does the probability of X>x given Y>y, which was answered for in part a. above, equal the probability of X>x mutiplied by Y>y

2.4 Mathematical Check for $P(X|Y) = P(X)P(Y)$

```r
X <- sum(prob.y.x$greaterLotArea)/ nrow(prob.y.x)
Y <- sum(prob.y.x$greaterSalePrice) / nrow(prob.y.x)
X * Y
```

```
## [1] 0.1875
```

```r
a == (X * Y)
```

```
## [1] FALSE
```

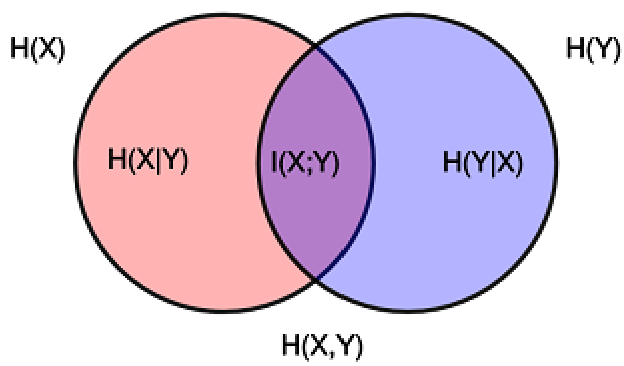
2.5 Chi Square test for association.

```r
prob.table <- as.data.frame(rbind(cbind(sum(prob.y.x$lesserLotArea), sum(prob.y.x$greaterLotArea)), cbi
chisq.test(prob.table)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  prob.table
## X-squared = 728, df = 1, p-value < 2.2e-16
```

> We see that the p-value is quite low, lower than the assumptive .05, so we therefore reject the null hypothesis that the values are independent of each other.

The below venn diagram from Wikipedia may provide a clearer understanding of the differences in these measures:



[^4]

[^4] By KonradVoelkel (Own work) [Public domain], via Wikimedia Commons

3 Descriptive and Inferential Statistics.

Provide univariate descriptive statistics and appropriate plots for both variables.

```r
description <- describe(sub.train.df["LotArea"])
latex(description, file = '')
```

sub.train.df["LotArea"]
1 Variables 1460 Observations

LotArea												
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	1073	1	10517	5718	3312	5000	7554	9478	11602	14382	17401

```
lowest :    1300    1477    1491    1526    1533, highest:  70761 115149 159000 164660 215245
```

The histogram in the upper right corner of the table shows a right skewed distribution, which is not surprising since houses in cities would likely have similar relatively smaller lot areas versus instances of large lot areas.

```r
description <- describe(sub.train.df["SalePrice"])
latex(description, file = '')
```

sub.train.df["SalePrice"]
1 Variables 1460 Observations

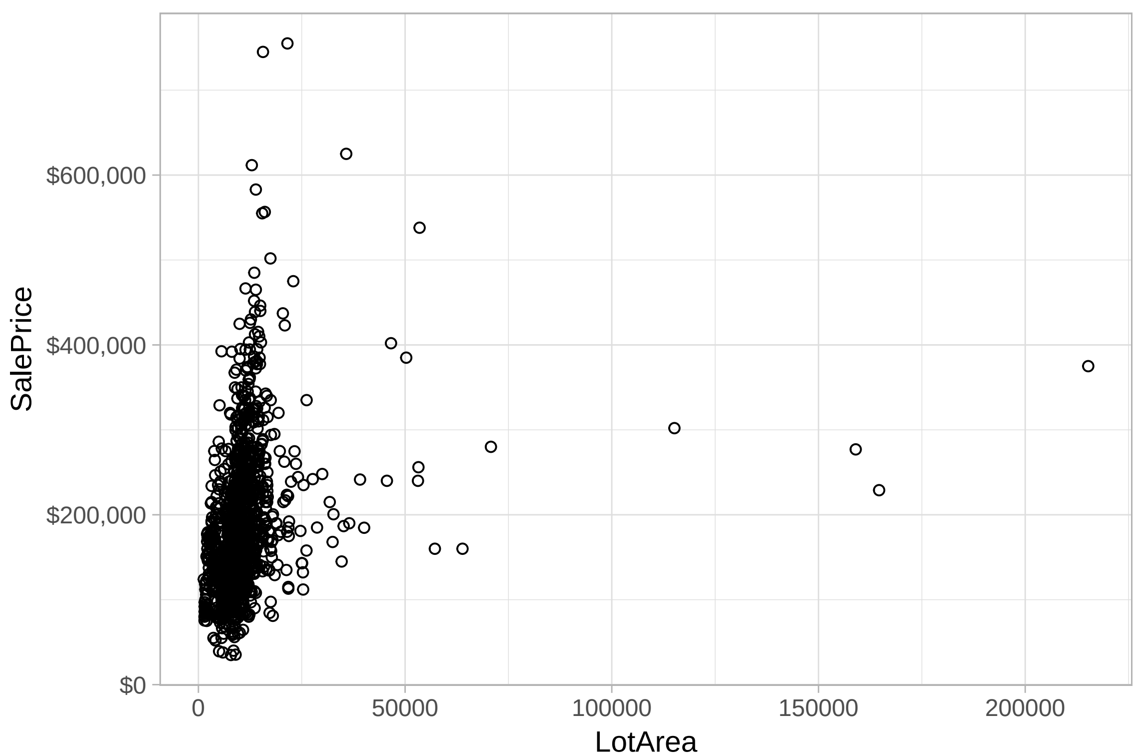
SalePrice												
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	663	1	180921	81086	88000	106475	129975	163000	214000	278000	326100

```
lowest :  34900  35311  37900  39300  40000, highest: 582933 611657 625000 745000 755000
```

As we can see from the histogram the shape of the data is near normal. It is interesting to visualize that lot area does not follow the same shape, this would hold with our original assumption that where the house is located has more impact than the size of the lot area.

Provide a scatterplot of X and Y.

```r
ggplot(sub.train.df, aes(x = LotArea, y = SalePrice)) + geom_point(shape = 1) +
    theme_light() + scale_y_continuous(labels = dollar)
```



Transform both variables simultaneously using Box-Cox transformations.

I am using the `BoxCox.lambda` function from the `forecast` package to determine the necessary transformations for the two variables.

```
library(forecast)
library(knitr)
l1 <- BoxCox.lambda(as.numeric(sub.train.df$SalePrice))
l2 <- BoxCox.lambda(as.numeric(sub.train.df$LotArea))

lamdas <- c(l1, l2)
Variables <- c("SalePrice", "LotArea")
dfBoxCox <- as.data.frame(cbind(round(as.numeric(lamdas),4), Variables))
colnames(dfBoxCox) <- c("$\\lambda$", "Variables")
kable(dfBoxCox, align = c("c", "c"))
```

λ	Variables
-0.3308	SalePrice
-0.1268	LotArea

Common Box-Cox Transformations[1] [2]

λ	Y'
-0.5	$Y^{-0.5} = \frac{1}{\sqrt{(Y)}}$
0	$\log(Y)$
.25	$\sqrt[4]{Y}$

Lambda values were truncated to the nearest tenth that match a common transformation as per the below table.

variable	variable transformation
SalePrice	$SalePrice^{-0.5}$
LotArea	$log(LotArea)$

3.1 Correlation Analysis

Using the transformed variables, run a correlation analysis and interpret.

```
sub.train.df.trans <- sub.train.df %>%
                      mutate(SalePrice = SalePrice^(-.5),
                             LotArea = log(LotArea))

sub.train.cor <- cor.test(sub.train.df.trans$SalePrice,
                          sub.train.df.trans$LotArea,
                          method = "pearson", conf.level = .99)
sub.train.cor
```

```
##
##  Pearson's product-moment correlation
##
## data:  sub.train.df.trans$SalePrice and sub.train.df.trans$LotArea
## t = -15.968, df = 1458, p-value < 2.2e-16
```

[1] Osborne, Jason W. "Improving your data transformations: Applying the Box-Cox transformation." Practical Assessment, Research & Evaluation 15.12 (2010): 1-9.

[2] By Understanding Both the Concept of Transformation and the Box-Cox Method, Practitioners Will Be Better Prepared to Work with Non-normal Data. . "Making Data Normal Using Box-Cox Power Transformation." ISixSigma. N.p., n.d. Web. 29 Oct. 2016.

```
## alternative hypothesis: true correlation is not equal to 0
## 99 percent confidence interval:
##  -0.4417063 -0.3269282
## sample estimates:
##        cor
## -0.3858091
```

> The p-value of the correlation test is 2.2e-16 which is less than the significance level of alpha at .05. We are using the standard alpha as there is no indication another any other value for alpha should be used. We can therefore say that the log of lot size and sale price raised to the -.5 power are significantly correlated with a negative correlation coefficient of -0.386.

Test the hypothesis that the correlation between these variables is 0 and provide a 99% confidence interval.

> The correlation test has specifically done that for us and we can safely reject the null hypothesis as we see that our 99% confidence interval exists at the values (-0.441, -0.327) with a p-value < 2.2e-16.

Discuss the meaning of your analysis.

> This means two possible things could have occured, there is no correlation and this data set is pulled from an unusual set of house sales. Or, more likely with the values obtained, our assumption of 0 correlation is incorect and we have obtained a very typical data set and must reject the null hypothesis because correlation does exist.

4 Linear Algebra and Correlation.

```
A <- cor(sub.train.df.trans)
kable(A)
```

	SalePrice	LotArea
SalePrice	1.0000000	-0.3858091
LotArea	-0.3858091	1.0000000

Invert your correlation matrix.(This is known as the precision matrix and contains variance inflation factors on the diagonal.)

```
B <- solve(A)
kable(B)
```

	SalePrice	LotArea
SalePrice	1.1748792	0.4532792
LotArea	0.4532792	1.1748792

Multiply the correlation matrix by the precision matrix, and then multiply the precision matrix by the correlation matrix.

```
corr.by.pre.M <- A %*% B
kable(corr.by.pre.M)
```

	SalePrice	LotArea
SalePrice	1	0

	SalePrice	LotArea
LotArea	0	1

```
pre.by.corr.M <- B %*% A
kable(pre.by.corr.M)
```

	SalePrice	LotArea
SalePrice	1	0
LotArea	0	1

5 Calculus-Based Probability & Statistics

Many times, it makes sense to fit a closed form distribution to data. For your non-transformed independent variable, location shift it so that the minimum value is above zero.

```
min(sub.train.df$LotArea)
```

[1] 1300

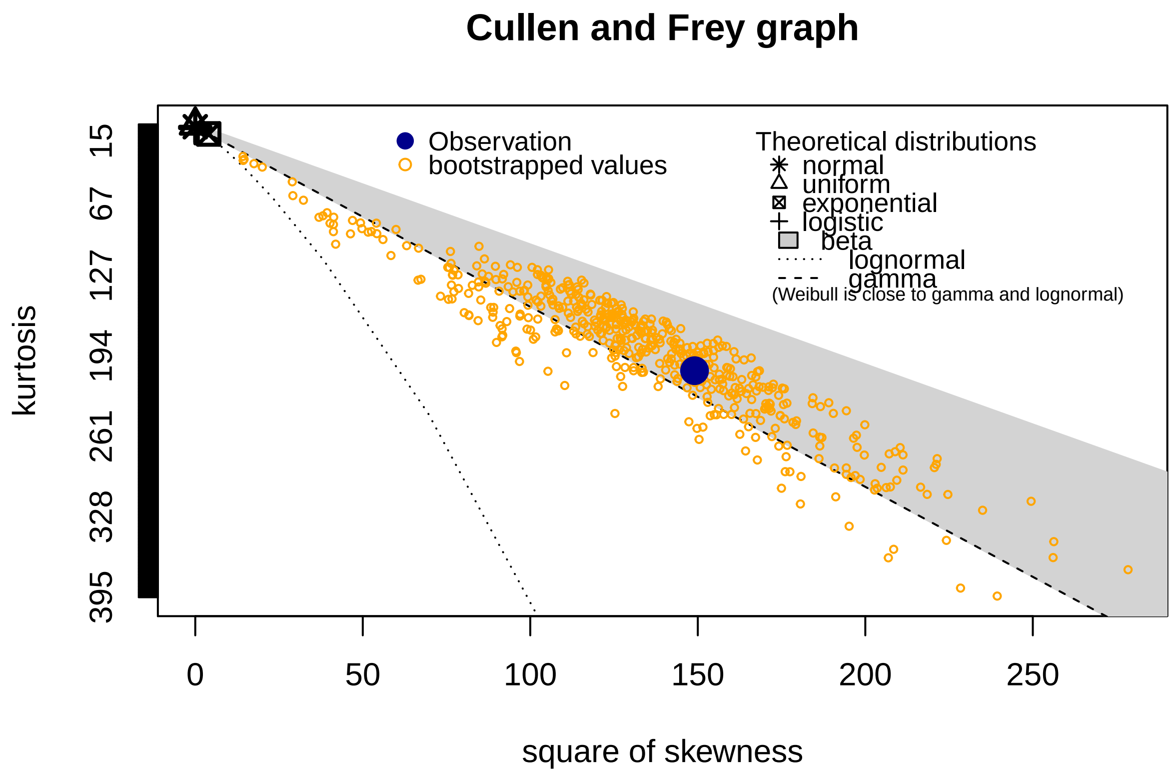
> For the independent variable chosen, there are no zero values observed. This makes sense as we would expect the lot area to have some value and I would expect it to never be unobserved (an assumption that at least estimates would be used without a true figure).
>
> However, if a shift was required something like the below could be used.

```
shift <- sub.train.df$LotArea + 1
```

Then load the MASS package and run fitdistr to fit a density function of your choice. (See https://stat.ethz.ch/R-manual/R-devel/library/MASS/html/fitdistr.html).

> First lets look at what distrubtion would best fit our data.

```
library(fitdistrplus)
descdist(sub.train.df$LotArea, discrete=FALSE, boot=500)
```



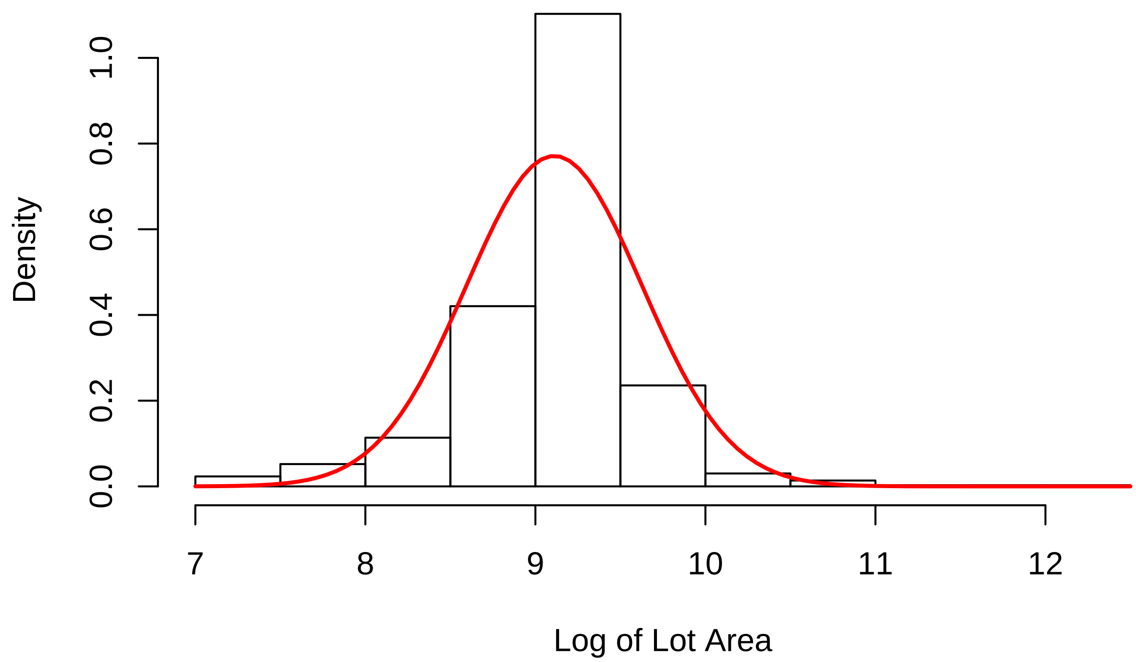

```
## summary statistics
## ------
## min:  1300   max:  215245
## median:  9478.5
## mean:  10516.83
## estimated sd:  9981.265
## estimated skewness:  12.20769
## estimated kurtosis:  206.2433
```

There were too many issues in attempting to fit the beta distribution so the next best theoretical distribution was used - log normal.

```
library(MASS)
fit.log <- fitdistr(sub.train.df$LotArea, densfun = "log-normal")
fit.log
```

```
##       meanlog         sdlog
##    9.110838240    0.517270830
##   (0.013537596) (0.009572526)
```

```
hist(log(sub.train.df$LotArea), prob=TRUE, xlab = "Log of Lot Area", main = "")
curve(dnorm(x, fit.log$estimate[1], fit.log$estimate[2]), col="red", lwd=2, add=T)
```



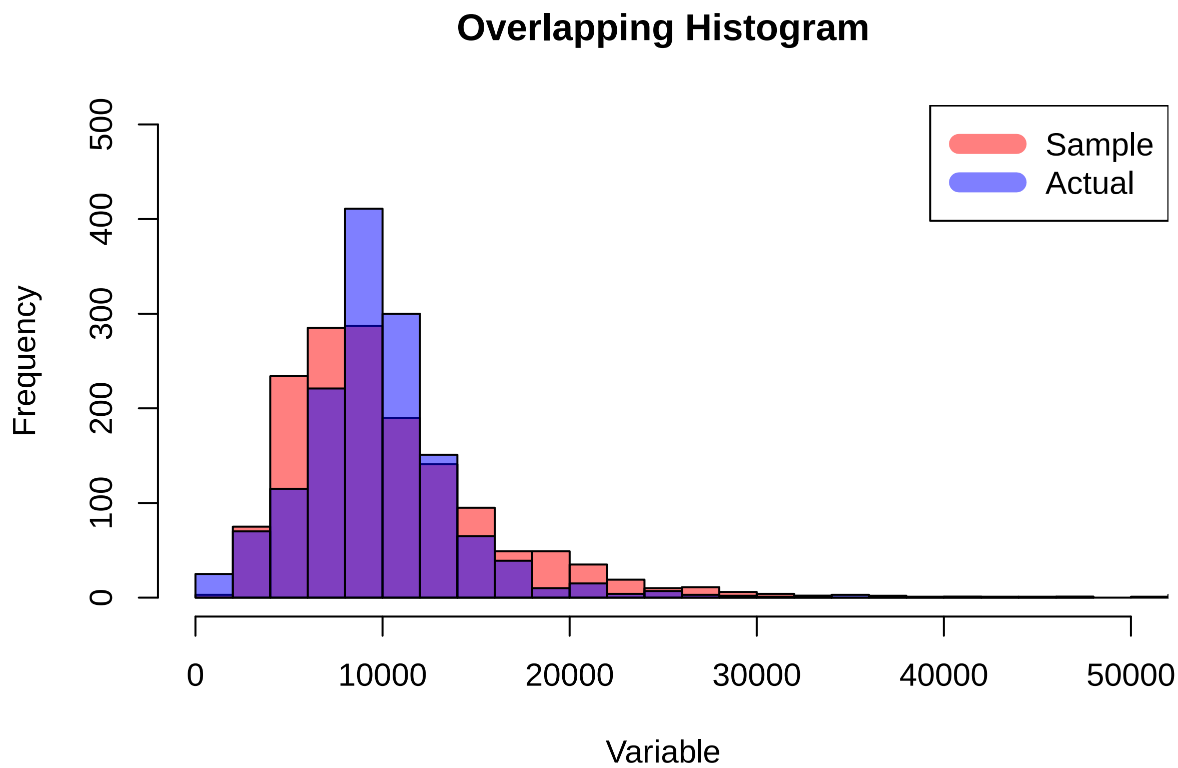
From our density plot, the distribution looks quite good.

Find the optimal value of the parameters for this distribution, and then take 1000 samples from this distribution (e.g., rexp(1000) for an exponential).

```
set.seed(1234)
sample <- rlnorm(1000, meanlog = fit.log$estimate[1], sdlog = fit.log$estimate[2])
```

Plot a histogram and compare it with a histogram of your non-transformed original variable.

```
hist(sample, pch = 20, breaks = 25, col = rgb(1,0,0,0.5), xlim = c(0,50000), ylim = c(0,500), main = 'O
hist(sub.train.df$LotArea, pch = 20, breaks = 100, col = rgb(0,0,1,0.5), add = T)
#https://www.r-bloggers.com/overlapping-histogram-in-r/
legend("topright", c("Sample", "Actual"), col=c(rgb(1,0,0,0.5), rgb(0,0,1,0.5)), lwd=10)
```



It is clear that the distributions are very similar. Plotting them overlapping gives a clear visual of how similar the distributions, note that x has been limited and does not extend out for extreme values of x.

6 Modeling

Build some type of regression model and submit your model to the competition board.

```
description <- describe(train.df %>% dplyr::select(-Id, -SalePrice))
latex(description, file = '')
```

train.df %>% dplyr::select(-Id, -SalePrice)
79 Variables 1460 Observations

MSSubClass

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	15	0.94	56.9	43.19	20	20	20	50	70	120	160

Value	20	30	40	45	50	60	70	75	80	85	90	120	160	180
Frequency	536	69	4	12	144	299	60	16	58	20	52	87	63	10
Proportion	0.367	0.047	0.003	0.008	0.099	0.205	0.041	0.011	0.040	0.014	0.036	0.060	0.043	0.007

Value	190
Frequency	30
Proportion	0.021

MSZoning

n	missing	distinct
1460	0	5

Value	C (all)	FV	RH	RL	RM
Frequency	10	65	16	1151	218
Proportion	0.007	0.045	0.011	0.788	0.149

LotFrontage

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1201	259	110	0.998	70.05	24.61	34	44	59	69	80	96	107

lowest : 21 24 30 32 33, highest: 160 168 174 182 313

LotArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	1073	1	10517	5718	3312	5000	7554	9478	11602	14382	17401

lowest :   1300   1477   1491   1526   1533, highest: 70761 115149 159000 164660 215245

Street

n	missing	distinct
1460	0	2

Value	Grvl	Pave
Frequency	6	1454
Proportion	0.004	0.996

Alley

n	missing	distinct
91	1369	2

Value	Grvl	Pave
Frequency	50	41
Proportion	0.549	0.451

LotShape

n	missing	distinct
1460	0	4

Value	IR1	IR2	IR3	Reg
Frequency	484	41	10	925
Proportion	0.332	0.028	0.007	0.634

LandContour

n	missing	distinct
1460	0	4

Value	Bnk	HLS	Low	Lvl
Frequency	63	50	36	1311
Proportion	0.043	0.034	0.025	0.898

Utilities

n	missing	distinct
1460	0	2

Value	AllPub	NoSeWa
Frequency	1459	1
Proportion	0.999	0.001

LotConfig

n	missing	distinct
1460	0	5

Value	Corner	CulDSac	FR2	FR3	Inside
Frequency	263	94	47	4	1052
Proportion	0.180	0.064	0.032	0.003	0.721

LandSlope

n	missing	distinct
1460	0	3

Value	Gtl	Mod	Sev
Frequency	1382	65	13
Proportion	0.947	0.045	0.009

Neighborhood

n	missing	distinct
1460	0	25

lowest : Blmngtn Blueste BrDale BrkSide ClearCr, highest: Somerst StoneBr SWISU   Timber Veenker

---

Condition1

n	missing	distinct
1460	0	9

Value	Artery	Feedr	Norm	PosA	PosN	RRAe	RRAn	RRNe	RRNn
Frequency	48	81	1260	8	19	11	26	2	5
Proportion	0.033	0.055	0.863	0.005	0.013	0.008	0.018	0.001	0.003

Condition2

n	missing	distinct
1460	0	8

Value	Artery	Feedr	Norm	PosA	PosN	RRAe	RRAn	RRNn
Frequency	2	6	1445	1	2	1	1	2
Proportion	0.001	0.004	0.990	0.001	0.001	0.001	0.001	0.001

BldgType

n	missing	distinct
1460	0	5

Value	1Fam	2fmCon	Duplex	Twnhs	TwnhsE
Frequency	1220	31	52	43	114
Proportion	0.836	0.021	0.036	0.029	0.078

HouseStyle

n	missing	distinct
1460	0	8

Value	1.5Fin	1.5Unf	1Story	2.5Fin	2.5Unf	2Story	SFoyer	SLvl
Frequency	154	14	726	8	11	445	37	65
Proportion	0.105	0.010	0.497	0.005	0.008	0.305	0.025	0.045

OverallQual

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	10	0.951	6.099	1.522	4	5	5	6	7	8	8

Value	1	2	3	4	5	6	7	8	9	10
Frequency	2	3	20	116	397	374	319	168	43	18
Proportion	0.001	0.002	0.014	0.079	0.272	0.256	0.218	0.115	0.029	0.012

OverallCond

n	missing	distinct	Info	Mean	Gmd
1460	0	9	0.814	5.575	1.111

Value	1	2	3	4	5	6	7	8	9
Frequency	1	5	25	57	821	252	205	72	22
Proportion	0.001	0.003	0.017	0.039	0.562	0.173	0.140	0.049	0.015

YearBuilt

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	112	1	1971	33.88	1916	1925	1954	1973	2000	2006	2007

lowest : 1872 1875 1880 1882 1885, highest: 2006 2007 2008 2009 2010

YearRemodAdd

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	61	0.997	1985	23.05	1950	1950	1967	1994	2004	2006	2007

lowest : 1950 1951 1952 1953 1954, highest: 2006 2007 2008 2009 2010

RoofStyle

n	missing	distinct
1460	0	6

Value	Flat	Gable	Gambrel	Hip	Mansard	Shed
Frequency	13	1141	11	286	7	2
Proportion	0.009	0.782	0.008	0.196	0.005	0.001

RoofMatl

n	missing	distinct
1460	0	8

Value	ClyTile	CompShg	Membran	Metal	Roll	Tar&Grv	WdShake	WdShngl
Frequency	1	1434	1	1	1	11	5	6
Proportion	0.001	0.982	0.001	0.001	0.001	0.008	0.003	0.004

Exterior1st

n	missing	distinct
1460	0	15

Value	AsbShng	AsphShn	BrkComm	BrkFace	CBlock	CemntBd	HdBoard	ImStucc	MetalSd	Plywood
Frequency	20	1	2	50	1	61	222	1	220	108
Proportion	0.014	0.001	0.001	0.034	0.001	0.042	0.152	0.001	0.151	0.074

Value	Stone	Stucco	VinylSd	Wd Sdng	WdShing
Frequency	2	25	515	206	26
Proportion	0.001	0.017	0.353	0.141	0.018

Exterior2nd

n	missing	distinct
1460	0	16

Value	AsbShng	AsphShn	Brk Cmn	BrkFace	CBlock	CmentBd	HdBoard	ImStucc	MetalSd	Other
Frequency	20	3	7	25	1	60	207	10	214	1
Proportion	0.014	0.002	0.005	0.017	0.001	0.041	0.142	0.007	0.147	0.001

Value	Plywood	Stone	Stucco	VinylSd	Wd Sdng	Wd Shng
Frequency	142	5	26	504	197	38
Proportion	0.097	0.003	0.018	0.345	0.135	0.026

MasVnrType

n	missing	distinct
1452	8	4

Value	BrkCmn	BrkFace	None	Stone
Frequency	15	445	864	128
Proportion	0.010	0.306	0.595	0.088

MasVnrArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1452	8	327	0.791	103.7	156.9	0	0	0	0	166	335	456

lowest : 0 1 11 14 16, highest: 1115 1129 1170 1378 1600

ExterQual

n	missing	distinct
1460	0	4

Value	Ex	Fa	Gd	TA
Frequency	52	14	488	906
Proportion	0.036	0.010	0.334	0.621

ExterCond

n	missing	distinct
1460	0	5

Value	Ex	Fa	Gd	Po	TA
Frequency	3	28	146	1	1282
Proportion	0.002	0.019	0.100	0.001	0.878

Foundation

n	missing	distinct
1460	0	6

Value	BrkTil	CBlock	PConc	Slab	Stone	Wood
Frequency	146	634	647	24	6	3
Proportion	0.100	0.434	0.443	0.016	0.004	0.002

BsmtQual

n	missing	distinct
1423	37	4

Value	Ex	Fa	Gd	TA
Frequency	121	35	618	649
Proportion	0.085	0.025	0.434	0.456

BsmtCond

n	missing	distinct
1423	37	4

Value	Fa	Gd	Po	TA
Frequency	45	65	2	1311
Proportion	0.032	0.046	0.001	0.921

BsmtExposure

n	missing	distinct
1422	38	4

Value	Av	Gd	Mn	No
Frequency	221	134	114	953
Proportion	0.155	0.094	0.080	0.670

BsmtFinType1

n	missing	distinct
1423	37	6

Value	ALQ	BLQ	GLQ	LwQ	Rec	Unf
Frequency	220	148	418	74	133	430
Proportion	0.155	0.104	0.294	0.052	0.093	0.302

BsmtFinSF1

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	637	0.967	443.6	484.5	0.0	0.0	0.0	383.5	712.2	1065.5	1274.0

lowest : 0 2 16 20 24, highest: 1904 2096 2188 2260 5644

BsmtFinType2

n	missing	distinct
1422	38	6

Value	ALQ	BLQ	GLQ	LwQ	Rec	Unf
Frequency	19	33	14	46	54	1256
Proportion	0.013	0.023	0.010	0.032	0.038	0.883

BsmtFinSF2

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	144	0.305	46.55	86.58	0.0	0.0	0.0	0.0	0.0	117.2	396.2

lowest : 0 28 32 35 40, highest: 1080 1085 1120 1127 1474

BsmtUnfSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	780	0.999	567.2	486.6	0.0	74.9	223.0	477.5	808.0	1232.0	1468.0

lowest : 0 14 15 23 26, highest: 2042 2046 2121 2153 2336

TotalBsmtSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	721	1	1057	459.5	519.3	636.9	795.8	991.5	1298.2	1602.2	1753.0

lowest : 0 105 190 264 270, highest: 3094 3138 3200 3206 6110

Heating

n	missing	distinct
1460	0	6

Value	Floor	GasA	GasW	Grav	OthW	Wall
Frequency	1	1428	18	7	2	4
Proportion	0.001	0.978	0.012	0.005	0.001	0.003

HeatingQC

n	missing	distinct
1460	0	5

Value	Ex	Fa	Gd	Po	TA
Frequency	741	49	241	1	428
Proportion	0.508	0.034	0.165	0.001	0.293

CentralAir

n	missing	distinct
1460	0	2

Value	N	Y
Frequency	95	1365
Proportion	0.065	0.935

Electrical

n	missing	distinct
1459	1	5

Value	FuseA	FuseF	FuseP	Mix	SBrkr
Frequency	94	27	3	1	1334
Proportion	0.064	0.019	0.002	0.001	0.914

X1stFlrSF 

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	753	1	1163	416.4	673.0	756.9	882.0	1087.0	1391.2	1680.0	1831.2

```
lowest :  334  372  438  480  483, highest: 2633 2898 3138 3228 4692
```

X2ndFlrSF 

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	417	0.817	347	450.2	0.0	0.0	0.0	0.0	728.0	954.2	1141.0

```
lowest :    0  110  167  192  208, highest: 1611 1796 1818 1872 2065
```

LowQualFinSF 

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	24	0.052	5.845	11.55	0	0	0	0	0	0	0

```
lowest :   0  53  80 120 144, highest: 513 514 515 528 572
```

GrLivArea 

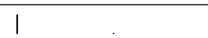
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	861	1	1515	563.1	848	912	1130	1464	1777	2158	2466

```
lowest :  334  438  480  520  605, highest: 3627 4316 4476 4676 5642
```

BsmtFullBath 

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.733	0.4253	0.5085

Value	0	1	2	3
Frequency	856	588	15	1
Proportion	0.586	0.403	0.010	0.001

BsmtHalfBath 

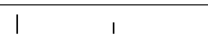
n	missing	distinct	Info	Mean	Gmd
1460	0	3	0.159	0.05753	0.1088

Value	0	1	2
Frequency	1378	80	2
Proportion	0.944	0.055	0.001

FullBath 

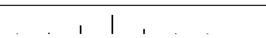
n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.766	1.565	0.5521

Value	0	1	2	3
Frequency	9	650	768	33
Proportion	0.006	0.445	0.526	0.023

HalfBath 

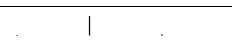
n	missing	distinct	Info	Mean	Gmd
1460	0	3	0.706	0.3829	0.4852

Value	0	1	2
Frequency	913	535	12
Proportion	0.625	0.366	0.008

BedroomAbvGr 

n	missing	distinct	Info	Mean	Gmd
1460	0	8	0.815	2.866	0.818

Value	0	1	2	3	4	5	6	8
Frequency	6	50	358	804	213	21	7	1
Proportion	0.004	0.034	0.245	0.551	0.146	0.014	0.005	0.001

KitchenAbvGr 

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.133	1.047	0.09174

Value	0	1	2	3
Frequency	1	1392	65	2
Proportion	0.001	0.953	0.045	0.001

KitchenQual

n	missing	distinct
1460	0	4

Value	Ex	Fa	Gd	TA
Frequency	100	39	586	735
Proportion	0.068	0.027	0.401	0.503

TotRmsAbvGrd

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	12	0.958	6.518	1.762	4	5	5	6	7	9	10

Value	2	3	4	5	6	7	8	9	10	11	12	14
Frequency	1	17	97	275	402	329	187	75	47	18	11	1
Proportion	0.001	0.012	0.066	0.188	0.275	0.225	0.128	0.051	0.032	0.012	0.008	0.001

Functional

n	missing	distinct
1460	0	7

Value	Maj1	Maj2	Min1	Min2	Mod	Sev	Typ
Frequency	14	5	31	34	15	1	1360
Proportion	0.010	0.003	0.021	0.023	0.010	0.001	0.932

Fireplaces

n	missing	distinct	Info	Mean	Gmd
1460	0	4	0.806	0.613	0.6566

Value	0	1	2	3
Frequency	690	650	115	5
Proportion	0.473	0.445	0.079	0.003

FireplaceQu

n	missing	distinct
770	690	5

Value	Ex	Fa	Gd	Po	TA
Frequency	24	33	380	20	313
Proportion	0.031	0.043	0.494	0.026	0.406

GarageType

n	missing	distinct
1379	81	6

Value	2Types	Attchd	Basment	BuiltIn	CarPort	Detchd
Frequency	6	870	19	88	9	387
Proportion	0.004	0.631	0.014	0.064	0.007	0.281

GarageYrBlt

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1379	81	97	1	1979	27.63	1930	1945	1961	1980	2002	2006	2007

lowest : 1900 1906 1908 1910 1914, highest: 2006 2007 2008 2009 2010

GarageFinish

n	missing	distinct
1379	81	3

Value	Fin	RFn	Unf
Frequency	352	422	605
Proportion	0.255	0.306	0.439

GarageCars

n	missing	distinct	Info	Mean	Gmd
1460	0	5	0.802	1.767	0.7609

Value	0	1	2	3	4
Frequency	81	369	824	181	5
Proportion	0.055	0.253	0.564	0.124	0.003

GarageArea

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	441	1	473	234.9	0.0	240.0	334.5	480.0	576.0	757.1	850.1

lowest : 0 160 164 180 186, highest: 1220 1248 1356 1390 1418

GarageQual

n	missing	distinct
1379	81	5

Value	Ex	Fa	Gd	Po	TA
Frequency	3	48	14	3	1311
Proportion	0.002	0.035	0.010	0.002	0.951

GarageCond

n	missing	distinct
1379	81	5

Value	Ex	Fa	Gd	Po	TA
Frequency	2	35	9	7	1326
Proportion	0.001	0.025	0.007	0.005	0.962

PavedDrive

n	missing	distinct
1460	0	3

Value	N	P	Y
Frequency	90	30	1340
Proportion	0.062	0.021	0.918

WoodDeckSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	274	0.858	94.24	125	0	0	0	0	168	262	335

```
lowest :   0  12  24  26  28, highest: 668 670 728 736 857
```

OpenPorchSF

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	202	0.909	46.66	62.43	0	0	0	25	68	130	175

```
lowest :   0   4   8  10  11, highest: 406 418 502 523 547
```

EnclosedPorch

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	120	0.369	21.95	39.39	0.0	0.0	0.0	0.0	0.0	112.0	180.1

```
lowest :   0  19  20  24  30, highest: 301 318 330 386 552
```

X3SsnPorch

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	20	0.049	3.41	6.739	0	0	0	0	0	0	0

Value	0	23	96	130	140	144	153	162	168	180	182	196	216	238
Frequency	1436	1	1	1	1	2	1	1	3	2	1	1	2	1
Proportion	0.984	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001

Value	245	290	304	320	407	508
Frequency	1	1	1	1	1	1
Proportion	0.001	0.001	0.001	0.001	0.001	0.001

ScreenPorch

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	76	0.22	15.06	28.27	0	0	0	0	0	0	160

```
lowest :   0  40  53  60  63, highest: 385 396 410 440 480
```

PoolArea

n	missing	distinct	Info	Mean	Gmd
1460	0	8	0.014	2.759	5.497

Value	0	480	512	519	555	576	648	738
Frequency	1453	1	1	1	1	1	1	1
Proportion	0.995	0.001	0.001	0.001	0.001	0.001	0.001	0.001

PoolQC

n	missing	distinct
7	1453	3

Value	Ex	Fa	Gd
Frequency	2	2	3
Proportion	0.286	0.286	0.429

Fence

n	missing	distinct
281	1179	4

Value	GdPrv	GdWo	MnPrv	MnWw
Frequency	59	54	157	11
Proportion	0.210	0.192	0.559	0.039

MiscFeature

n	missing	distinct
54	1406	4

Value	Gar2	Othr	Shed	TenC
Frequency	2	2	49	1
Proportion	0.037	0.037	0.907	0.019

MiscVal

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	21	0.103	43.49	85.67	0	0	0	0	0	0	0

Value	0	50	350	400	450	500	550	600	700	800	1150	1200	1300	1400
Frequency	1408	1	1	11	4	10	1	5	5	1	1	2	1	1
Proportion	0.964	0.001	0.001	0.008	0.003	0.007	0.001	0.003	0.003	0.001	0.001	0.001	0.001	0.001

Value	2000	2500	3500	8300	15500
Frequency	4	1	1	1	1
Proportion	0.003	0.001	0.001	0.001	0.001

MoSold

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
1460	0	12	0.985	6.322	3.041	2	3	5	6	8	10	11

Value	1	2	3	4	5	6	7	8	9	10	11	12
Frequency	58	52	106	141	204	253	234	122	63	89	79	59
Proportion	0.040	0.036	0.073	0.097	0.140	0.173	0.160	0.084	0.043	0.061	0.054	0.040

YrSold

n	missing	distinct	Info	Mean	Gmd
1460	0	5	0.955	2008	1.498

Value	2006	2007	2008	2009	2010
Frequency	314	329	304	338	175
Proportion	0.215	0.225	0.208	0.232	0.120

SaleType

n	missing	distinct
1460	0	9

Value	COD	Con	ConLD	ConLI	ConLw	CWD	New	Oth	WD
Frequency	43	2	9	5	5	4	122	3	1267
Proportion	0.029	0.001	0.006	0.003	0.003	0.003	0.084	0.002	0.868

SaleCondition

n	missing	distinct
1460	0	6

Value	Abnorml	AdjLand	Alloca	Family	Normal	Partial
Frequency	101	4	12	20	1198	125
Proportion	0.069	0.003	0.008	0.014	0.821	0.086

In the variable listing we see many columns with NA values. To simplify our model lets exclude any columns with NAs.

```
library(leaps)
train.df.2 <- train.df[ , colSums(is.na(train.df)) == 0]
subsetModel <- regsubsets(SalePrice ~ ., data = train.df.2,
                          nbest = 1, really.big = T,  method = "seqrep")
```

```
## Reordering variables and trying again:
```

```
summary <- summary(subsetModel, matrix.logical = TRUE)
kable(t(summary$outmat))
```

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
Id	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
MSSubClass	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE
MSZoningFV	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
MSZoningRH	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
MSZoningRL	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
MSZoningRM	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotArea	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
StreetPave	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotShapeIR2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotShapeIR3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotShapeReg	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LandContourHLS	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LandContourLow	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LandContourLvl	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
UtilitiesNoSeWa	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotConfigCulDSac	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotConfigFR2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotConfigFR3	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LotConfigInside	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LandSlopeMod	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LandSlopeSev	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodBlueste	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodBrDale	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodBrkSide	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodClearCr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodCollgCr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodCrawfor	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodEdwards	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodGilbert	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodIDOTRR	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodMeadowV	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodMitchel	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodNAmes	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodNoRidge	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE
NeighborhoodNPkVill	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodNridgHt	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE
NeighborhoodNWAmes	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodOldTown	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodSawyer	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodSawyerW	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodSomerst	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodStoneBr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
NeighborhoodSWISU	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodTimber	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
NeighborhoodVeenker	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1Feedr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1Norm	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1PosA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1PosN	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1RRAe	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

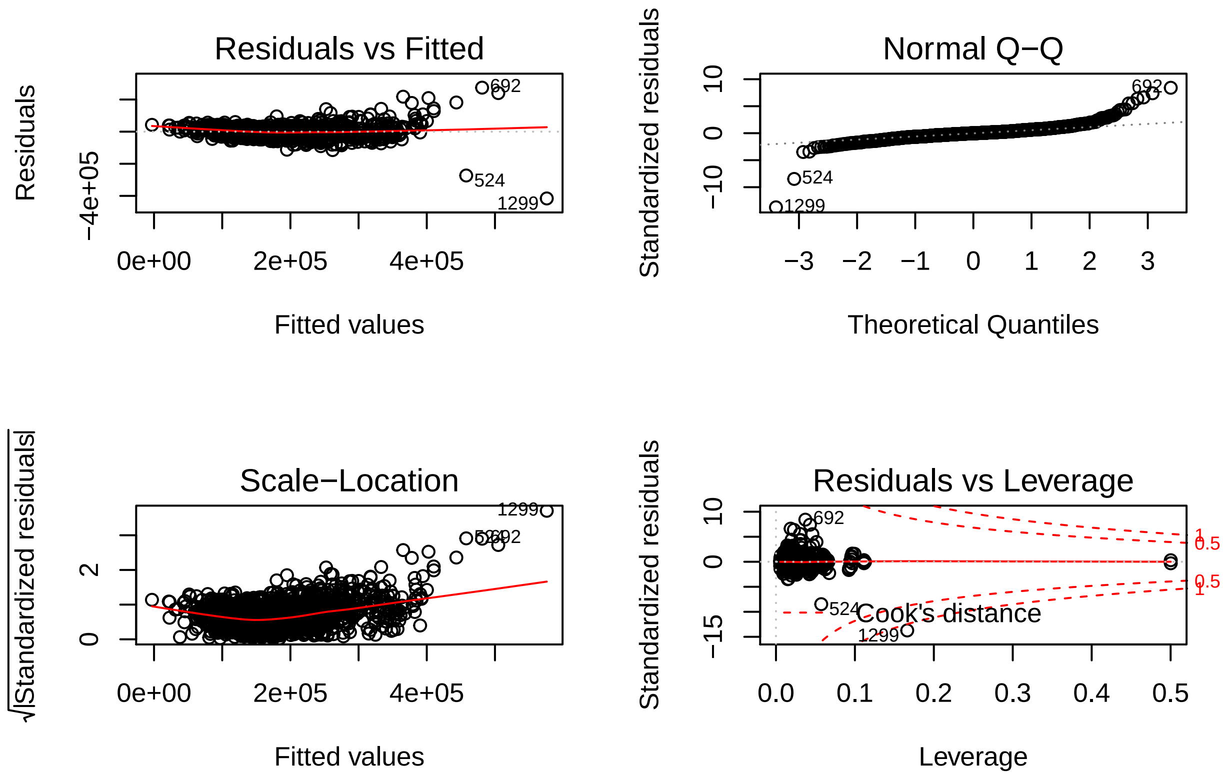
	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
Condition1RRAn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1RRNe	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition1RRNn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2Feedr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2Norm	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2PosA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2PosN	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2RRAe	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2RRAn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Condition2RRNn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BldgType2fmCon	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BldgTypeDuplex	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BldgTypeTwnhs	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BldgTypeTwnhsE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyle1.5Unf	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyle1Story	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyle2.5Fin	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyle2.5Unf	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyle2Story	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyleSFoyer	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HouseStyleSLvl	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
OverallQual	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
OverallCond	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
YearBuilt	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	FALSE
YearRemodAdd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE
RoofStyleGable	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofStyleGambrel	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofStyleHip	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofStyleMansard	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofStyleShed	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlCompShg	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlMembran	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlMetal	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlRoll	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlTar&Grv	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlWdShake	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
RoofMatlWdShngl	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stAsphShn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stBrkComm	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stBrkFace	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stCBlock	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stCemntBd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stHdBoard	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stImStucc	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stMetalSd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stPlywood	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stStone	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stStucco	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stVinylSd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stWd Sdng	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior1stWdShing	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndAsphShn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
Exterior2ndBrk Cmn	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndBrkFace	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndCBlock	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndCmentBd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndHdBoard	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndImStucc	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndMetalSd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndOther	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndPlywood	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndStone	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndStucco	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndVinylSd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndWd Sdng	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Exterior2ndWd Shng	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterQualFa	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterQualGd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterQualTA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterCondFa	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterCondGd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterCondPo	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ExterCondTA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FoundationCBlock	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FoundationPConc	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FoundationSlab	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FoundationStone	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FoundationWood	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BsmtFinSF1	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
BsmtFinSF2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BsmtUnfSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
TotalBsmtSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingGasA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingGasW	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingGrav	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingOthW	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingWall	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingQCFa	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingQCGd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingQCPo	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HeatingQCTA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
CentralAirY	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
X1stFlrSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
X2ndFlrSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
LowQualFinSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
GrLivArea	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
BsmtFullBath	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BsmtHalfBath	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FullBath	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
HalfBath	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
BedroomAbvGr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
KitchenAbvGr	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
KitchenQualFa	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
KitchenQualGd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

	1 (1)	2 (1)	3 (1)	4 (1)	5 (1)	6 (1)	7 (1)	8 (1)	9 (1)
KitchenQualTA	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
TotRmsAbvGrd	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FunctionalMaj2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FunctionalMin1	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FunctionalMin2	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FunctionalMod	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FunctionalSev	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
FunctionalTyp	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
Fireplaces	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
GarageCars	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE
GarageArea	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
PavedDriveP	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
PavedDriveY	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
WoodDeckSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
OpenPorchSF	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
EnclosedPorch	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
X3SsnPorch	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
ScreenPorch	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
PoolArea	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
MiscVal	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
MoSold	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
YrSold	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeCon	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeConLD	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeConLI	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeConLw	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeCWD	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeNew	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeOth	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleTypeWD	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleConditionAdjLand	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleConditionAlloca	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleConditionFamily	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleConditionNormal	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
SaleConditionPartial	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

Based on the last best model we will limit the data set to the following variables MSSubClass, Neighborhood-NoRidge, NeighborhoodNridgHt, NeighborhoodStoneBr, OverallQual, YearRemodAdd, BsmtFinSF1, GrLivArea, GarageCars.

```r
library(DAAG)
fit <- lm(SalePrice ~ MSSubClass + Neighborhood + OverallQual + YearRemodAdd + BsmtFinSF1 + GrLivArea +
p <- par(mfrow=c(2,2))
plot(fit)
```




```r
par(p)
```

I am slightly concerned that the residual plot does not look like a shotgun pattern. My assumption is that the high influence points and/or outliers may be impacting the model. Outlier treatment may improve the model but the model is currently sufficient for our purposes.

```r
library(car)
library(data.table)
lmfit <- setDT(as.data.frame(car::vif(fit)), keep.rownames = TRUE)[]
lmfit$Adjusted_GVIF <- (lmfit$`GVIF^(1/(2*Df))`^2)
kable(lmfit, align = c("l", "c", "c", "c", "c"))
```

rn	GVIF	Df	GVIF^(1/(2*Df))	Adjusted_GVIF
MSSubClass	1.412246	1	1.188379	1.412246
Neighborhood	5.575916	24	1.036450	1.074228
OverallQual	3.035516	1	1.742273	3.035516
YearRemodAdd	1.786865	1	1.336737	1.786865
BsmtFinSF1	1.231322	1	1.109649	1.231322
GrLivArea	1.980075	1	1.407151	1.980075
GarageCars	1.928807	1	1.388815	1.928807

Using GVIF^(1/(2*Df)) [3] in order to verify that the VIF threshold of 5 for multicollinearity is not exceed. Fortunately, we find that no variable exceeds the threshold and we do not need to adjust for multicollinearity.

[3] “Which Variance Inflation Factor Should I Be Using: $GVIF$ or $textGVIF^{1/(2cdottextdf)}$?” R. N.p., n.d. Web. 13 Nov. 2016.

6.1 The final model

```r
stargazer(fit, header = FALSE, no.space = TRUE,
          style = "all2", font.size = "normalsize",
          single.row = TRUE, intercept.bottom = FALSE)
```

Table 8:

	Dependent variable:
	SalePrice
Constant	−621,777.700*** (111,442.300)
MSSubClass	−252.678*** (24.405)
NeighborhoodBlueste	−12,510.880 (24,882.880)
NeighborhoodBrDale	−16,417.030 (11,866.240)
NeighborhoodBrkSide	−14,640.440 (9,753.068)
NeighborhoodClearCr	7,771.633 (10,647.930)
NeighborhoodCollgCr	−8,855.995 (8,742.258)
NeighborhoodCrawfor	7,447.104 (9,729.488)
NeighborhoodEdwards	−24,629.000*** (9,317.138)
NeighborhoodGilbert	−12,303.590 (9,065.933)
NeighborhoodIDOTRR	−25,820.490** (10,379.870)
NeighborhoodMeadowV	1,205.989 (11,879.710)
NeighborhoodMitchel	−18,072.460* (9,692.696)
NeighborhoodNAmes	−18,834.730** (8,971.063)
NeighborhoodNoRidge	40,530.480*** (10,050.780)
NeighborhoodNPkVill	−9,409.847 (13,823.590)
NeighborhoodNridgHt	49,514.520*** (9,100.426)
NeighborhoodNWAmes	−21,429.510** (9,344.861)
NeighborhoodOldTown	−31,650.010*** (9,111.020)
NeighborhoodSawyer	−19,047.140** (9,502.205)
NeighborhoodSawyerW	−15,759.290* (9,404.611)
NeighborhoodSomerst	7,011.384 (8,880.182)
NeighborhoodStoneBr	55,104.420*** (10,602.380)
NeighborhoodSWISU	−27,693.620** (11,081.320)
NeighborhoodTimber	3,500.186 (9,974.428)
NeighborhoodVeenker	25,505.000* (13,027.270)
OverallQual	16,039.450*** (1,094.370)
YearRemodAdd	310.102*** (56.246)
BsmtFinSF1	23.326*** (2.113)
GrLivArea	52.970*** (2.326)
GarageCars	11,974.750*** (1,614.394)
Observations	1,460
R^2	0.829
Adjusted R^2	0.826
Residual Std. Error	33,181.540 (df = 1429)
F Statistic	231.137*** (df = 30; 1429) (p = 0.000)
Note:	*p<0.1; **p<0.05; ***p<0.01

Provide your complete model summary and results with analysis.

Report your Kaggle.com user name and score.